Convolutional Neural Networks and Transfer Learning for Quality Inspection of Different Sugarcane Varieties

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***Abstract*—In this article, we employed computer vision and deep learning techniques to select and plant healthy billets, which increased plant population and the yield per hectare of sugarcane planting. We employed well-known convolutional neural network architectures to process large image data sets and transfer learning techniques to expand the results to different sugarcane varieties. It would be very time consuming to collect and label large data sets for each sugarcane variety, for which quality inspection is needed, prior to planting. We used a two-step transfer learning process to extend the trained architecture to new varieties. We compared results obtained during transfer learning using AlexNet, VGG-16, GoogLeNet, and ResNet101 architectures to classical computer vision methods. Our goal was to determine the best approach to detect damaged and good billets in the shortest processing time. Best results in both time and accuracy were obtained with AlexNet. For AlexNet, we compared the permutations of three sugarcane varieties in order to find the best model to identify the healthy sugarcane billets. We then reduced the number of images employed to retrain the model to determine the tradeoff between time and performance. Ultimately, one needs only a few dozen billets of the new variety to retrain the network. Our approach led to meaningful increments in the yield per hectare ranging from 33 to 80% depending on sugarcane variety.**

***Index Terms*—Agricultural robotics, computer vision, convolutional neural networks (CNNs), sugarcane, transfer learning.**

I. Introduction

AN INCREASING population has placed a greater demand for the agricultural industry to produce greater quantities of food. However, the number of individuals that actually produce food has continually decreased since. The 2017 census of agriculture reported a decrease in the number of farms, farmers, and farmland in the United States [1]. The solution to this problem will require a combination of higher crop yields and an increase in crop production efficiency. Farmers will need to utilize technology to meet these demands and robotics may offer a significant part of this solution. Computer vision and image processing is a key aspect of many agricultural robotics applications [2], such as weed control, field scouting, harvesting, and yield prediction. These applications encompass the combination of computer vision with machine learning techniques [3] and, recently, deep learning approaches have grown in popularity with convolutional neural networks (CNNs) being the preferred approach for detection and task recognition [4] even in agriculture [5]. Here, we use CNNs in a large image data set to inspect and classify three sugarcane varieties.

Sugarcane is a tropical grass that grows worldwide, and it is primarily used in sugar production. The total world sugarcane production in 2017 was 1 841 528 388 t, which was produced on 25 976 935 hectares [6]. When the farmers use mechanized combine harvesters to cut sugarcane into small segments, called “billets” for planting, the billets are often damaged with cracks, crushed parts, or their buds are affected [7]. Plant pathogens can enter through the damaged parts and adversely affect the sugarcane billets. Prior to the mechanization of the planting process, one harvested hectare of seed cane would allow eight hectares to be planted. Post mechanization of the damaged billets required doubling the planting density with estimates that one harvested hectare allows for the planting of approximately three to four hectares. The work in [7] confirmed that damaged billets greatly impact the outcome in the planting process, significantly diminishing the productivity as the damaged billets could have been diverted to the mills for sugar production. Here, we focus on expanding the inspection process of harvested billets with deep learning prior to planting.

There are many varieties of sugarcane. For example, in Louisiana, there are 12 commercially grown varieties [8]. These varieties are quite different in terms of dimensions and characteristics, making it difficult to detect the damaged features when employing a deterministic method developed for a single

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variety. Thus, it is important to develop a robotic solution using computer vision and deep learning to automatically detect the damaged billets, irrespective of the variety, and send them to the mills. To train and adapt the deep learning methods to detect the damaged billets, it is necessary to have a data set with at least hundreds or even thousands of images for each new variety. The labeling necessary to train these methods depends on an exhaustive manual process done by experts in sugarcane to classify the billets according to the class of damage. It would be necessary to capture the images, preprocess them to the correct resolution, and then train the deep learning model while examining performance in estimation and detection tests to generate the final system to be used in real time. This is quite a time consuming and costly process to repeat every time we have to classify a new variety. To address this limitation, we developed a two-step approach employing a CNN and transfer learning method to detect defects and outperform classical computer vision (CCV) methods. Here we report on the approach: first, we performed an exhaustive comparative analysis on the transfer learning of different CNN architectures to select the one that best detects the defect, and second, we determined the minimum number of images required to expand and retrain the CNN.

CNN in agriculture [5] was primarily employed in plant recognition [9]–[13], fruit detection [14]–[20] (mainly on apples [16], [17], sweet peppers [16], [19], and mangoes [15]), and weeding (mainly in sugar beet crops [21], [22]). The aforementioned literature focuses on the detection of the whole fruit, plant, or weed. None of the writing is about the quality inspection or detailed analysis of fruit or plant damage. For quality inspection, it is necessary to capture the images at a very short distance. There is some recent work on plant phenotyping using CNNs for the specific features of wheat or other crops (e.g., [23]), and in identifying disease on the leaves of different plant species, such as [24]. We found very few articles on quality or detecting an immature fruit [19]. The work in [7] is the only one that made a quality analysis of sugarcane billets but was limited to only one variety and used CCV methods, obtaining good results in the detection of the damaged billets but with the high levels of false positives. To the best of our knowledge, our article represents the first attempt on the quality inspection of different sugarcane varieties using CNNs looking for damage introduced by combine harvesters.

Furthermore, most of these prior studies arbitrarily selected the CNN architecture. Two well-known CNN architectures widely used in agriculture are AlexNet [9], [10], [13], [14], [23], [24] and VGG-16 [15]–[17], [19], [20], [22], [24]. Others used the GoogLeNet architecture, such as [13], [24], and ResNet with its different architectures (e.g., [12], [18]). There were a few attempts to compare two [13], four [12], or even five [24] different CNN architectures. Here, we performed an exhaustive comparative analysis on the transfer learning of four CNN architectures versus a CCV solution. Our goal is to find the best performer in identifying most of the damaged billets while minimizing the number of samples so as to retrain the CNN with good performance for a new variety.

TABLE I
PERCENTAGES OF DAMAGED BILLETS AND GOOD BILLETS

Variety	% of damaged billets	% of good billets
HoCP 09-804	33.38	66.62
HoCP 96-540	52.75	47.25
L 01-299	53.50	46.50

Proportion per variety.

II. Data Collection

We collected a large data set of images, which served as the basis for all our experiments. Our data set is publicly available[1].

A. Data Set

We collected a sample of different sugarcane varieties between September 24 and 26, 2018, in Houma, Louisiana, USA, at the USDA Sugarcane Research Unit Farm. The team of sugarcane experts from the USDA included a Research Agronomist, a Biological Science Technician, two Agricultural Science Research Technicians, and a Biological Science Aid. The sugarcane varieties selected were as follows:

1) the L 01-299, which is the most widely grown variety in Louisiana by acreage;
2) the HoCP 09-804, is a more recent variety than L 01-299, with greener and thinner stalks;
3) the HoCP 96-540, is an older variety with thicker stalks than either L 01-299 or HoCP 09-804.

Our experts suggested that HoCP 09-804 would likely be less damaged during harvesting because of its small size. Each variety was harvested in the early morning hours with a combine harvester, employing a wagon for transport.

B. Damaged Versus Good Billets

To determine the proportion of damaged billets versus good billets for the three different varieties, we collected from the wagon 8 buckets each with 100 billets for a total sample of 800 billets. Experts classified good and damaged billets. The percentage of damaged billets per variety was determined. The damaged billets were further separated into five classes of billets: cracked, crushed, no buds, two buds, single-damaged bud. Quality control during a secondary inspection eliminated any misclassification prior to capturing and processing the images. The percentages of damaged and good billets for the three varieties are summarized in Table I.

C. Collected Images

For HoCP09-804 and HoCP96-540 varieties, we collected at least 120 billets for each of the five damage classes. We collected the images for all billets with a high resolution (5 MP) Blackfly S color camera (FLIR Systems, Wilsonville, OR, USA).

[1][Online]. Available: https://github.com/The77Lab/SugarcaneDeepLearning.

TABLE II
NUMBER OF COLLECTED BILLETS

Variety	Total billets	Damaged billets	Good billets
HoCP 09-804	1397	864	533
HoCP 96-540	1072	679	393
L 01-299	405	242	163

Number of billets per variety and per class.

Fig. 1. Top row: damaged (left) and good billets (right) of the variety HoCP 09-804. Central row: damaged (left) and good billets (right) of the HoCP 96-540. Bottom row: damaged (left) and good billets (right) of the L 01 299.

To reduce image collection time, each image consisted mainly of five carefully placed billets showing the damage. A total of 578 images with a total of 2874 billets were collected in three days. Our goal is to find the minimum number of billets from one variety necessary to properly classify the billets of other varieties. Table II lists the number of billets collected for each type of class for the three varieties.

The USDA experts suggested that if a billet was covered by leaves, it should be considered as good billet. To confirm that, after capturing the images, a sample of 100 billets covered by leaves were taken from each variety. All the leaves were removed and we determined that only four (out of 100) were damaged billets for the HoCP 09-804 and HoCP 96-540 varieties, and none for the L 01-299 variety.

Fig. 1 shows the examples of captured images of damaged and good billets of each variety. Note the different colors and textures of each variety. We employed preprocessing and segmentation for the three varieties. We separated the cropped billets from the raw images into two classes: "damaged" and "good" for each variety. These images were the inputs for the CNN models.

III. Deep Learning for Quality Inspection of Sugarcane

A. Deep Learning

Classical machine learning applications to task classification require a lot of expert knowledge and manual fine-tuning to design the feature extractors that will classify the input images into the desired classes [4]. Deep learning is a form of machine learning that allows complex computational models to learn features in multiple layers. The most used deep learning method in computer vision is the CNN [4]. CNN is a type of deep neural network with different types of layers that creates different representations of the data from the most general to the most specific as the layers get deeper [5]. The learning process needs a training stage, which uses big data sets of images from which the network will learn the features. Usually, only the last layers of the CNNs are fully connected so that each layer can be trained with less interference. This improves speed.

Depending on the number and type of layers, there are different CNN architectures. Instead of arbitrarily selecting a popular CNN architecture, we performed a comparative analysis of several CNN architectures applied to our problem to detect the quality of the sugarcane billets. We selected the four most used CNN architectures in agriculture: AlexNet created by Krizhevsky [25] (with a depth of 8 and 25 layers in total), VGG-16 developed by Simonyan and Zisserman [26] (with a depth of 16 and 41 layers in total), GoogLeNet made by Szegedy *et al.* [27] (with a depth of 22 and 144 layers in total), and ResNet generated in all its versions by He *et al.* [28] (we are using ResNet101 with a depth of 101 and 347 layers in total). Those four CNN architectures cover a wide spectrum of models from a few layers to many and different depths among other characteristics.

B. Transfer Learning

In classical machine learning, we would need to train the system every time with a new data set, which is not efficient and takes too much time [see an example for three varieties in Fig. 2(a)]. Transfer learning, also known as knowledge transfer, is used to reduce the need and effort to collect the labeled data set or augment it [29]. In many real-world applications, it is expensive or impossible to collect large data sets for all possible classes. Transfer learning improves the learning of a new task through the transfer of knowledge from a related task that has already been learned. In the case of the four popular CNN architectures selected, they were already pretrained with more than one million images of around 1000 classes [30]. Even when those classes are different objects—e.g., vehicles, animals—the models are very useful to extract features on the images and the retraining of these models is done in a much shorter time.

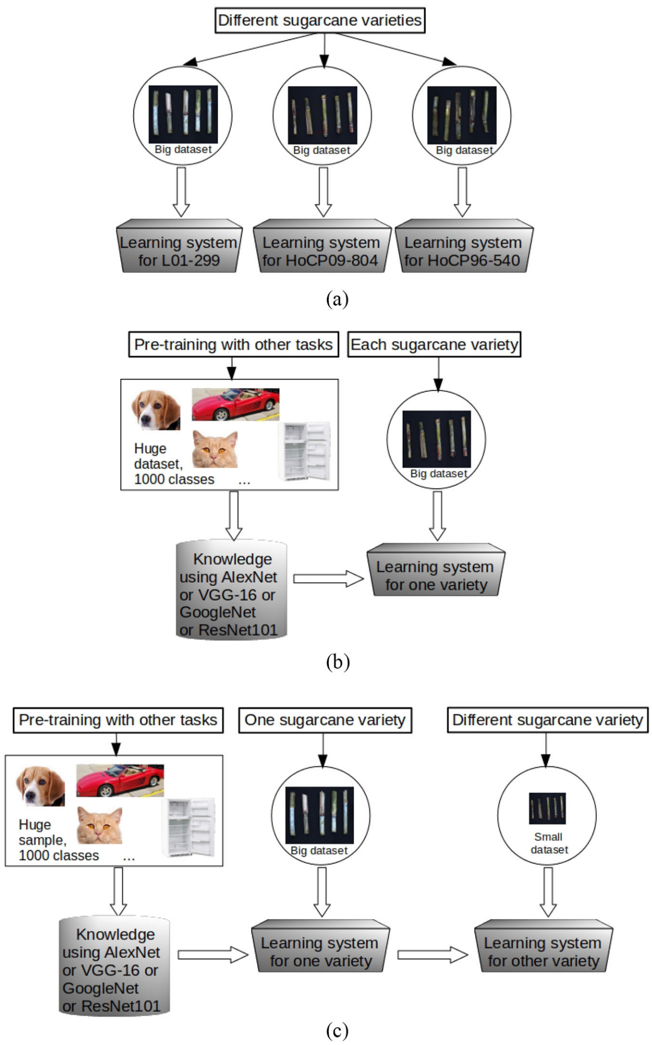

Fig. 2. Three schemes summarizing different options applied to our problem. (a) Classical machine learning. (b) One-step transfer learning. (c) Two-step transfer learning.

We modified the last fully connected layer of each of the four architectures (AlexNet, VGG-16, GoogLeNet, and ResNet101) to have only two neurons (instead of 1000) that represent our two classes. Instead of training the models from scratch with our data sets, those four pretrained popular models could be used to improve the learning [as depicted in Fig. 2(b)]. However, it would be necessary that experts manually classify hundreds if not a thousand sugarcane billets every time to retrain the CNN model. This would not be practical in the field as it would be time intensive. Instead, we propose to take advantage of transfer learning in two steps to create an automatic process that could allow any farmer to use it for any sugarcane variety [see Fig. 2(c)]. In the first step, we transfer the knowledge obtained by AlexNet, VGG-16, GoogLeNet or ResNet101 to the task of sugarcane quality detection. The data set of a sugarcane variety is used to retrain the selected CNN architecture. As a second step, a new CNN model is retrained with a new data set of another variety to transfer the learning to that one. We ran the tests for all the permutations of the three harvested sugarcane varieties. The first step was done for all four CNN architectures, each architecture with each of the three sugarcane varieties. From there, the model that had the highest values of true negative rate (TNR used for all the correctly classified defective billets), of true positive rate (TPR used for all the correctly classified healthy billets), and of Matthews correlation coefficient (MCC used for the overall calculation) to increase productivity and reduce processing time to train and the test was chosen. MCC is a statistical score typically employed for the binary classifications of unbalanced data sets (our case) [31]. MCC is a better choice than others, such as the ACC (Accuracy commonly used in CNNs in agriculture), because it has a high value only if true positives, true negatives, false negatives, and false positives had good results. The MCC ranges between -1 (worst prediction) and 1 (best prediction), where an MCC of 0 indicates that the prediction could be obtained randomly. The second step was made only for that chosen model. In other words, we repeated six times the flow shown at the bottom of Fig. 2 for the chosen CNN model.

C. Increase in Productivity

Presently farmers double the density of billets planted in furrows to account for the large percentage of damaged ones. Considering the percentages of healthy and damaged billets listed in Table I for every sugarcane variety and the potential deep learning improvement, we can approximately calculate the increase in productivity. If the new percentage of healthy billets is much larger than the percentage of the bad ones, then the density does not have to be duplicated when planting. That allows us to plant a larger area, thus increasing productivity. In addition to the TNR, TPR, and MCC, an important value is that the percentage of increase of the good billets to be planted (this means the difference between the old percentage and the new one after detection) that will correspond to the percentage of decrease of the damaged billets that will no longer be planted. For example: Assume we have 10 000 sugarcane billets harvested from the L 01-299 variety to test our system. We know that 5350 billets are damaged and 4650 are good billets (see Table I). Suppose the system gives us a TNR of 0.8 for the damaged billets and a TPR of 0.7 for the good billets. Then, we have detected 4280 damaged billets that can be removed, and only 1070 damaged billets that were not removed. Also, we correctly detected 3255 good billets. In the new total of billets to be planted, we will have 4325. The new proportion of damaged billets to be planted is just 24.74% compared with 53.5% of damaged billets in the original sample. The new proportion of good billets to be planted is 75.26%, an increment of 28.76% with respect to the 46.5% of good billets in the original sample. In this way, we could recommend redirecting more harvested billets to our system. The billets removed are not wasted because they are sent to the mill to generate more sugar.

IV. Results

Experts determined the appropriateness of sugarcane billets for planting. We then trained different CNN architectures to identify the billet quality and compared their performance

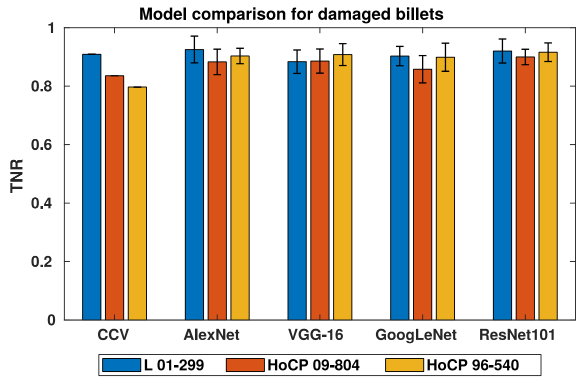

Fig. 3. TNR comparative results of five models to detect damaged sugarcane billets for the three varieties. The TNR value range is from 0 to 1.

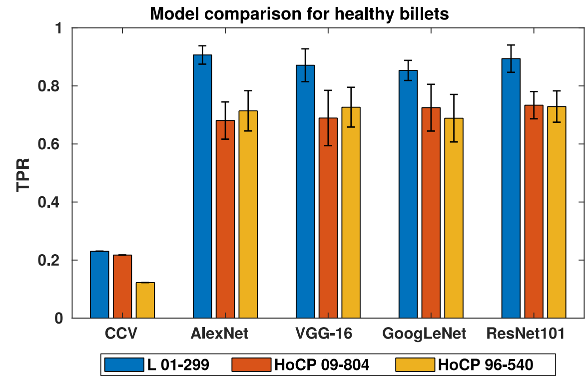

Fig. 4. TPR comparative results of five models to detect healthy sugarcane billets for the three varieties. The TPR value range is from 0 to 1.

against the CCV method. We then discussed the improvement in terms of yield per hectare.

A. Experimental Setup

We used the deep learning MATLAB toolbox in an Alienware Aurora high-end computer with Intel Core i7-9700HQ, 32 GB of RAM, NVIDIA graphics card GeForce RTX 2070 with 2304 CUDA cores, 8 GB of video memory, with Linux Ubuntu Studio 18.04.3 and MATLAB R2019b.

We speeded up the procedure by 12 to 13 times by using the graphics processing unit (GPU) instead of the CPU for the training and testing of the CNN models. All the results reported were obtained using the GPU.

B. Comparison Between Several CNN Architectures and CCV Methods

We tested the data set of the three sugarcane varieties implementing the CCV method in [7] in order to detect the damaged features in the sugarcane billets. We compared these results with those of the four different CNN models for the three varieties. To have a diversity of scenarios with different data set sizes and to compare all the different CNN models, we ran all the experiments of this section 12× with the random selection of the subset of images for training, validation, and evaluation.

To compare AlexNet, VGG-16, GoogLeNet, and ResNet101, we randomly split each data set of the three varieties: 60% for training, 20% for validation, and 20% for evaluation or testing. After several tests with different values, we got the best performance training all the models with an initial learning rate of 0.001, a maximum number of epochs of 50, a minibatch size of 32, a patience value of 5 in validation stopping, and shuffling the training data every epoch. This is the first step in the transfer learning process. Fig. 3–8 compare the results obtained with the four CNN models and the CCV method. For all figures with TNR, TPR, and MCC values, the height of each bar represents the mean and the error bars in black correspond to the standard deviation.

The CCV method had the lowest performance. It is a deterministic method focused on finding the damaged billets for the L 01-299 variety and it generated many false positives. The four selected architectures gave results in a similar range (TNR, TPR, MCC, and percentage of the good billets to plant) but ResNet101 and AlexNet were the ones with the best results for different sugarcane varieties. However, ResNet101 took too much processing time (around 10 to 20 times longer). Hence, AlexNet was the best option for our system.

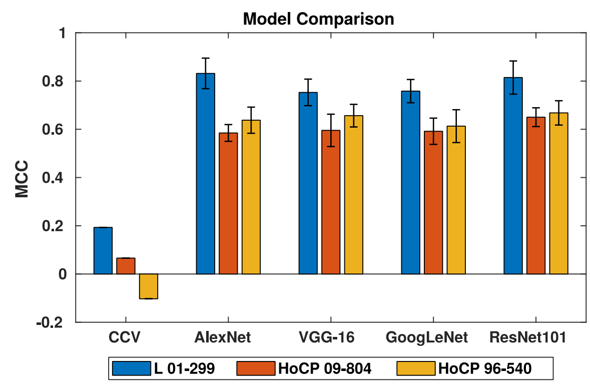

Fig. 5. MCC comparative results of five models to detect damaged sugarcane billets for the three varieties. The MCC value range is from −1 to 1.

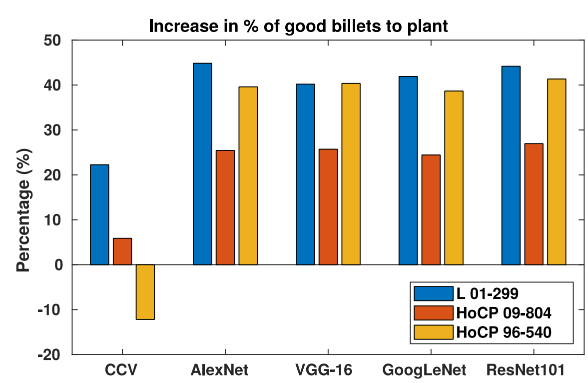

Fig. 6. Comparative results of the four CNN models and CCV showing the improvement in the percentage of good billets to plant.

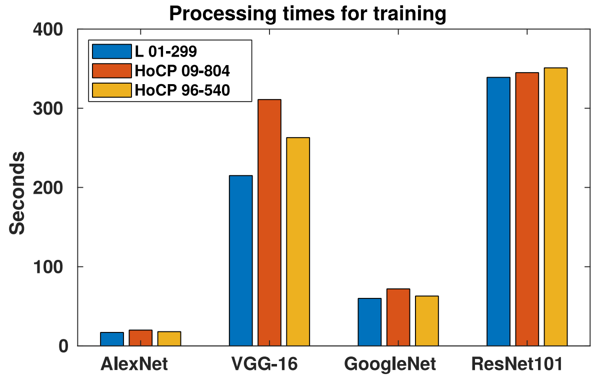

Fig. 7. Comparative results about processing times in seconds to train the four CNN models for each sugarcane variety.

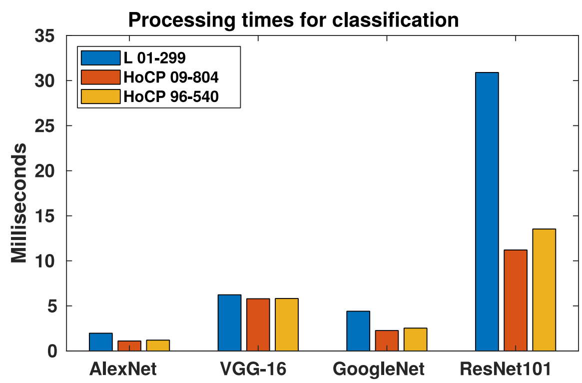

Fig. 8. Comparative results about processing times in milliseconds to evaluate the four CNN models for each sugarcane variety.

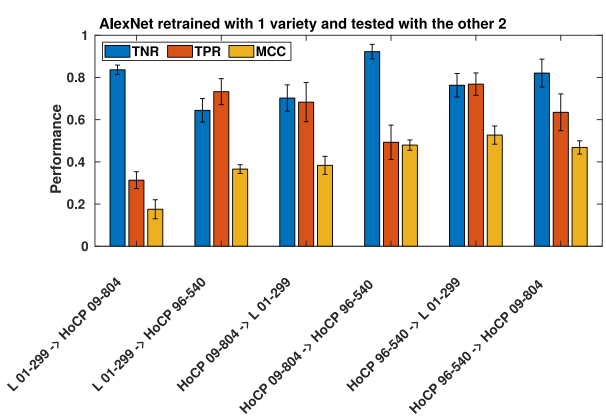

Fig. 9. Performance results (TNR, TPR, and MCC) of AlexNet retrained with each sugarcane variety (the first variety on each X-axis label) and tested with the other two sugarcane varieties (the second variety on each X-axis label).

C. One-Step Transfer Learning

With those AlexNet models retrained to detect the three sugarcane varieties, we did the comparative analysis of the six permutations of the sugarcane varieties. First, we ran the six cases with an AlexNet model pretrained with each variety and tested the prediction with the other two varieties. We summarized in Fig. 9– and 10 the results for those cases with only one-step transfer learning. We retrained AlexNet with 80% of the images of the data set of each variety with the remaining

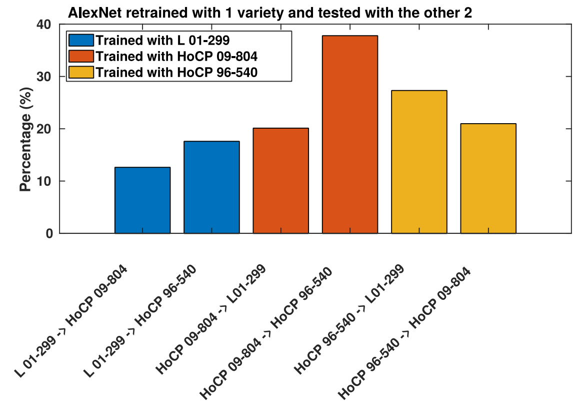

Fig. 10. Comparative results of the increase in percentage of good billets to plant, retraining AlexNet with each sugarcane variety (the first variety on each X-axis label) and testing with the other two sugarcane varieties (the second variety on each X-axis label).

20% of the images used for validation. We dedicated 100% of the data set images of the other two varieties for testing.

Comparing the results of Fig. 3–6 and 9 and 10, we can see how the performance drops when we are trying to detect the damages in one sugarcane variety having trained the AlexNet model with the other variety. It should be clear that we need the second step of transfer learning. We started the second step of the process using transfer learning from one variety to another, checking what is the minimum number of sugarcane billets required to improve the results.

D. Two-Step Transfer Learning

For the second step of transfer learning, we tested with small percentages of billets of each data set (variety) incrementally, 1 to 5% one by one, and 5 until 30% five by five. Half of those corresponding percentages were used as an extra amount of images for validation. We tested those experiments in four different ways for the corresponding AlexNet model retrained with the first variety: without freezing any layer, freezing the first two convolutional layers, freezing all the five convolutional layers, and freezing six layers (the first fully connected layer and all convolutional layers).

We summarized in Table III the best two cases for each of the three varieties, among the six permutations, that require the smallest number of images to retrain the corresponding model and also good increment of the percentage of good billets to plant. The second column refers to the corresponding increase in percentage for each variety (the same variety to train, validate, and test)—see also Fig. 6. The third to the fifth columns show how the values of the second column drop when the variety to be tested is different from the one that was trained—see also Fig. 10. The last four columns show the best two results for different small percentages of images to retrain in two steps. For the three varieties, 10% of images to train (plus 5% to validate) was the best case. For some cases, 3% or 5% is also good to consider if the farmers want to decrease further the number of images required to retrain the network. Indeed, these cases offer the best results for the three varieties in terms of improvement of the production while requiring the smallest number of images.

TABLE III
RESULTS FOR THE THREE VARIETIES

Variety to test	1 TL %	1 TL %	1 TL %	1 TL %	2 TL %	2 TL %	2 TL variety used	#
L 01-299	44.8	-	20.1	27.3	35.96	5	HoCP 96-540	6
					37.46	10	HoCP 96-540	2
HoCP 09-804	25.4	12.6	-	21	21.81	3	HoCP 96-540	2
					23.42	10	HoCP 96-540	0
HoCP 96-540	39.6	17.6	37.8	-	34.50	3	HoCP 09-804	5
					36.16	10	HoCP 09-804	0

Comparing one-step transfer learning and two-step transfer learning in terms of percentage increase of good billets (TL = Transfer learning). The last column includes the number of frozen layers for the corresponding case.

V. DISCUSSION

Our goal was to detect in the shortest possible time the damaged features with the minimum number of images to retrain the network in order to plant mainly healthy billets. The best performance in terms of processing times is achieved with AlexNet and the worst with VGG-16 and ResNet101. In several applications, the amount of data to retrain a deep learning system is limited. One way to solve this problem is to create synthetic data to augment the data set. In our case, due to the great diversity of textures of each billet for the three varieties, it was not possible to do this task without eliminating the damaged features that we wanted to identify. Instead, we employed the two-step transfer learning process, which decreased the amount of data required.

For the two-step transfer learning process, we can say the following as regards each variety.

1) For the sugarcane variety L 01-299 (training in the first step with the variety HoCP 96-540): The first option is to use in the second step only 30 billets (7.5%: 5% to train + 2.5% to validate) obtaining an increase of 35.96% in the number of good billets to plant (from 46.5% to 82.46%). Instead of planting 4 hectares, we could plant over 7 hectares (increment in the production of around 80%). The second option is to retrain the system in the 2nd step with 60 billets (10 + 5%), obtaining an increase of 37.46% in the number of good billets. We could plant over 7 hectares (increment in the production of 80.5%, almost the same as with 5% of images to train).
2) For the sugarcane variety HoCP 09-804 (training in the first step with the variety HoCP 96-540): One option is to only need about 63 billets in the second step (3 + 1.5%), corresponding to an increase in the production of around 32.7%. Another option is to train the second step with 210 billets (10 + 5%), which represents an increment in the production of approximately 35.1%.
3) For the sugarcane variety HoCP 96-540 (training in the first step with the variety HoCP 09-804): Around 48 billets (3% + 1.5%) could be used in the second transfer learning, obtaining around 73% increment in production. Another possibility is to retrain the system with roughly 161 billets (10% + 5%), to get an increment of 76.5% more or less.

It is important to note that the average of the processing times measured to retrain the system in the second step is between 2 and 10 s. Considering the cases with the least number of billets for each variety, the processing times are between 1 and 2 s. An automatic system, based on the two-step transfer learning with AlexNet, can be developed. The system would be previously pretrained with one of the more common sugarcane varieties. Then, the system would receive as input one billet at a time (indicating in some graphical interface if the billet is damaged or good), collecting a minimum number of billets for retraining, prior to widespread use in the field. Good parallel to the proposed approach is the need for calibrating a device prior to use.

VI. CONCLUSION

In this article, we demonstrated that the use of deep learning delivers much better results in terms of performance than the CCV method. We doubled the performance for L 01-299 variety, quintupled the performance for the HoCP 09-804 variety, and got a much superior result for the HoCP 96-540, for which the classical method did not work well. The popular CNN models (AlexNet, VGG-16, GoogLeNet, and ResNet101) were pretrained with very large data sets, which helped to retrain faster to obtain better results. As the layers of the CNN models increased in number, the processing time increased rapidly. Hence, there was a tradeoff between a processing time and performance. Among the models that were compared, AlexNet proved to be the best option to perform quality inspection on sugarcane billets. AlexNet was implemented in a two-step process of transfer learning and led to around 22× less billets to retrain the network for a new sugarcane variety. Every time it is necessary to harvest and plant a new sugarcane variety, a farmer could quickly classify a minimum number of billets of the new variety (around 50 billets) and retrain the system leading to improvements of 33 to 80% as compared to without the system. Deep learning, specifically AlexNet CNN and transfer learning in two steps, may allow a farmer to classify the quality of the sugarcane billets and afford planting ∼7 new hectares of sugarcane instead of the present 4 hectares.

One must take our results with the appropriate caveats. There might be errors due to preprocessing manual tasks at the beginning of data collection. We plan to account for these errors in the future estimates of the performance.

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